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Energy-Aware Framework for Underwater Mine Detection System Using Underwater Acoustic Wireless Sensor Network

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Abstract: Underwater mines are considered a major threat to aquatic life, submarines, and naval activities. Detecting and locating these mines is a challenging task, due to the nature of the underwater environment. The deployment of underwater acoustic sensor networks (UWASN) can provide an efficient solution to this problem. However, the use of these self-powered sensors for intensive data sensing and wireless communication is often energy-scaring and might call into question the viability of their application. One attractive solution to extend the underwater wireless sensor network will be the adoption of cluster-based communication, since data processing and communication loads are distributed in a timely manner over the members of the cluster. In this context, this study proposes an energy-efficient solution for high-accuracy underwater mine detection based on the adequate clustering approach. The proposed scheme uses a processing approach based on wavelet transformation to extract relevant features to efficiently distinguish mines from other objects using the Naïve Bayes algorithm for classification. The main novelty of this approach is the design of a new low-complexity scheme for efficient sensor-based acoustic object detection that outperforms most of the existing solutions. It consumes a low amount of energy, while ensuring 95.12% target detection accuracy.

Keywords: underwater mine detection; acoustic wireless sensor network; clustered UWSNs; wavelet transformation; sonar signal

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1. Introduction

The recognition and detection of underwater mines is an active research field motivated by the need to clear mines, due to their harmful effects on the environment [1]. An underwater mine is a destructive object that represents a significant threat to human and marine life [2,3]. Many systems for detecting underwater mines have been developed to reduce the negative impact of their explosion. However, almost all of the existing methods require sophisticated, expensive equipment to explore the sea and/or human operators to maintain an ideal system. Therefore, a detection system is needed that improves the efficiency of the mine clearance process, with a significant reduction in the operational time, cost, and the system operator's risk of injury or loss of life, and with high detection accuracy.

Wireless sensor networks (WSN) hold great potential for aquatic environment monitoring, since they can sense, gather, and transmit data without a physical connection [2,4]. Although, in a roundabout way, this has led to the development of a new self-driven device called underwater wireless sensor networks (UWSNs) [5], they are considered an alternative to manual operations, such as cable interactions and aquatic systems, for implementations (e.g., self-directed underwater vehicles (AUVs) and autonomous underwater vehicle management) [1]. These systems provide an attractive solution for the low-cost continuous monitoring of underwater environments [4,6–8]. Underwater acoustic sensor networks (UWASN) can be applied for the detection of underwater mines. Furthermore, these devices incorporate sensors and other components that can send and receive different signals. They can communicate through acoustic waves, which are used to build and deploy UWSN systems in deep underwater settings.

The sensor nodes have strong limitations in their processing ability, embedded battery power, wireless bandwidth, and storage space. The major obstacle that calls into question the feasibility of applications built on these sensors is the energy constraint. Therefore, in order to extend the sensor battery lifetime, a low-complexity scheme for data processing and communication is required [9,10]. The clustering approach is one of the practical solutions to managing network energy consumption efficiently [11]. It also helps to distribute the energy consumption among the nodes in the network. The working mechanism for this approach involves grouping the sensor nodes into the cluster and electing one of these nodes to be the cluster head. The cluster head is responsible for gathering the data from its members and sending them to the base station.

In most cases, the nodes will be deployed densely to cover all of the required areas, which makes some of the nodes enter sleep mode, thereby reducing the energy consumption. The use of a cluster-based architecture helps to share the processing load via the sensors of the cluster, which consequently reduces the per-node energy consumption and contributes to extending the network lifetime. Furthermore, the application of the clustering approach assists in reducing the amount of sent information, which increases the network lifetime [12,13]. A critical aspect of the proposed approach is represented by the need to perform advanced signal processing at the sensors, which entails significant energy consumption and makes the feature extraction mechanism essential to reduce energy consumption. Furthermore, the energy-aware design of systems solving complex problems requires efficient management of energy consumption without losing performance, which is carried out at a design level by solving the optimization problems involving energy consumption as a metric [12,14–18]. In the UWSN, the transmission process consumes more energy compared with sensing or computation processes. It consumes approximately 80% of the power for each sensor node [12]. Thus, if we minimize the size of the data, it will reduce the energy consumption of each node.

Compared to terrestrial WSNs, underwater environments are characterized by unique features and face several issues, such as the depth-related impact on temperature, salinity, pressure, winds, and waves. These characteristics significantly affect the high-frequency waves used to collect sea-environment information (e.g., EM waves), which suffer from severe attenuation when used. Similarly, low-frequency signals, such as optical waves, need high-precision pointing beams, which suffer from scattering.

Underwater signal acquisition methods should have the capability to resist seawater characteristics. For an underwater medium, acoustic waves are less lossy and support long-range signal transmission. Thus, acoustic signals are primarily employed in underwater communication. Sound is a series of pressure perturbations that travel as a wave and exhibit phenomena such as reflection, diffraction, and interference [15]. Sonar sensors are considered an efficient choice because of their low fabrication cost and low power consumption. Moreover, sonar signals suffer less attenuation compared to other underwater techniques [16]. Developing a successful underwater mine detection system requires that mines can be distinguished (or classified) from other mine-like objects with great accuracy. Therefore, there is a solid need to extract the relevant information from the sonar data in order to evaluate and understand the signal properly. So-called feature extraction directly affects a system's classification performance [19]. If the extracted features are not expressive for a certain problem, then the classification is not satisfactory [20]. At present, numerous techniques have been proposed for these subjects, including spectrogram correlation, time-frequency analysis, hidden Markov models, wavelet transformation (WT), and other approaches. The WT of signals has been widely employed for feature extraction. It converts the signals into a time or frequency domain, and the resultant wavelet coefficients can be used for classification [19]. Compared to the other feature extraction techniques—such as slop vector waveform, Fourier transforms, and chaos methods—WT consumes less energy, as it extracts the expressive information from the original signal.

In this context, the main contribution of this research paper is to propose a clustered underwater wireless acoustic sensor network (UWASN) for mine detection. This system is designed to be lightweight and to reduce energy consumption, while automating the whole procedure of detecting and monitoring aquatic environments efficiently. The system provides the following characteristics:

1. Effective, lightweight mine detection using the wavelet-based extracted features of sonar signals.
2. Precise mine surveillance systems and short mine monitoring.

The rest of this paper is structured as follows: Section 2 presents a comprehensive study and review of the related works on detecting underwater mines based on sonar signals. It also reviews the studies of clustered UWSNs. Section 3 presents the UWASN energy consumption model. Section 4 demonstrates the proposed scheme. Section 5 provides different sensing methods. Section 6 covers the experiment setup implementation and the simulation environment. Section 7 contains an evaluation of the results, and the conclusions with recommendations for future work are presented in Section 8.

2. Methodology and Related Work

2.1. Methodlogy

In the design and evaluation of the proposed underwater mine detection scheme, we adopted the methodology shown in Figure 1. The specification of the tasks involved in the processing of the received acoustic signal is performed taking into account the accuracy of detection, as well as low-complexity constraints. Several machine learning classification methods will be assessed in terms of the accuracy of mine detection.

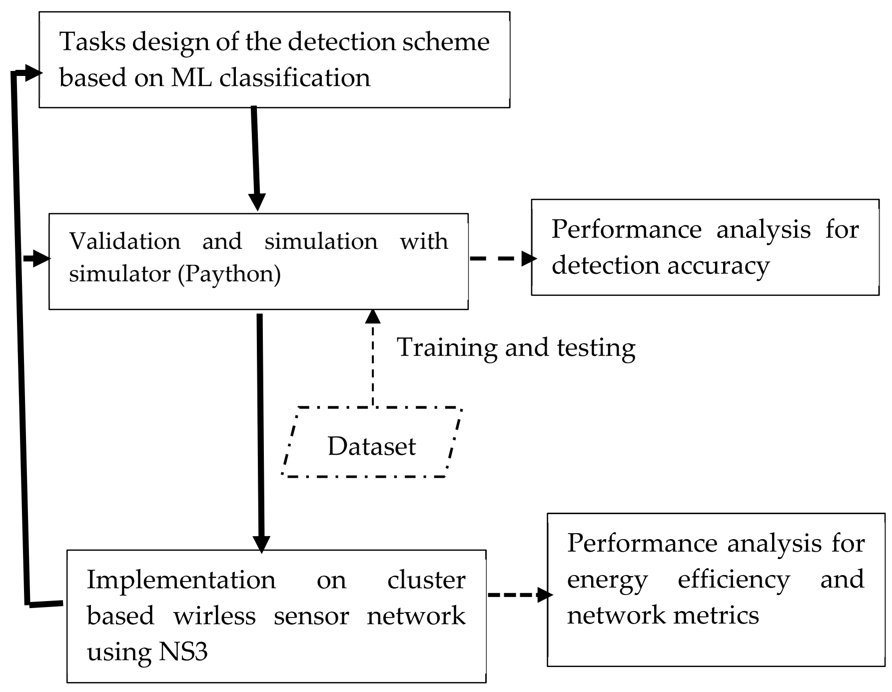

Figure 1. General adopted methodology.

The proposed scheme implemented with Python is evaluated in terms of detection accuracy based on the available dataset. It is then implemented under NS3 over a cluster-based WSN to evaluate the energy efficiency and to estimate the network performance metrics.

2.2. Related Work

This study aims to explore submerged wireless sensor networks. It delivers a complete analysis of connected works and their implementation in locating and detecting underwater mines. UWSNs may be quickly created if certain features are met, as evidenced by this article [19]. Therefore, the main objective of this study is to explain the various circumstances and how UWSNs can be designed in a special manner to efficiently manage and use the available energy in the process of identifying and clearing underwater minefields to enable the acquisition of a safe and healthy marine environment. In this section, we recapitulate some of the most relevant publications on distinguishing underwater mines from other objects using the WT of sonar data and works that have adopted clustered UWASNs for mine detection. The other areas studied include the detection of imagery regarding underwater objects and energy-resource management in UWSNs. Thus, a comprehensive review of the relevant literature should support the successful development of UWSNs for sea mine detection.

2.2.1. Attainment of Submerged Signals and Feature Extraction

The effectiveness of the WT of sonar signals for feature extraction has been extensively investigated and studied. The research has shown that WT exceeds other techniques in providing accurate results. Therefore, we studied works that have adopted WT to classify underwater mines.

WT has been employed as the activation function in certain deep learning models, and it has been proven to be successful [21]. To find the coefficient of a signal, the authors used a discrete Fourier transform and converted it to a sparse form, resulting in complex data. Complex-valued Haar and complex-valued Mexican hat are the wavelet activation functions used for the classification in the neural network. The researchers measured the accuracy of their work when running it with tenfold cross-validation (CV) and when splitting the data into 50% for training and 50% for testing. The accuracy values were 94.23% and 95.19%, respectively.

As an added bonus, a binary multistage classifier, which is a cascading series of classifiers that engage the Daubechies WT as the feature route, uses the extracted coefficients by using the Daubechies WT as the feature vector [22]. The authors tested their approach with wavelet levels ranging from two to thirty, using various extracted features. They were able to achieve an accuracy rate of 88%.

Battula et al. [23] proposed a data mining wavelet decision tree (WT tree) framework. It transforms sonar sounds using discrete Haar WT and then supplies the modified signals to the classifier for classification. As a first step, they used a learning procedure to identify the best features for classification. After that, they converted the features using Haar WT. This reduced the feature size and eliminated the misclassified characteristics. As a result, their categorization accuracy was correct 82.82% of the time.

2.2.2. Clustered UWASNs

Exploration has recently focused on the clustering mechanisms of underwater acoustic sensor nodes (UWASNs), owing to the critical importance of achieving the highest possible energy efficiency, given that underwater environments pose more significant challenges to preserving the sensor node battery [24–26]. Therefore, we investigated the design and qualities of the previously created works.

UWSNs use a lot of energy, thus, scientists have recommended data aggregation and a round-based clustering strategy to cut down consumption [27]. The CH was chosen based on the following two factors: the node's residual energy and the distance from the BS. Next, in the clustering formation, the CH sends an invitation message to all of its neighbors to join its cluster. In the end, the author used the Euclidean distance technique to see how similar the received and stored data were after receiving data from the cluster members and limiting transmissions. One of the two data packets was directed to the BS for further processing once a certain degree of similarity had been attained. According to the simulation's outcomes, less energy was spent. This mechanism may lead to an energy imbalance between the nodes.

Three different communication paradigms are supported by the clustered routing system developed by Yadav et al. [15], which is built on three diverse communication paradigms, including the acoustic, free-space optical (FSO), and EM. The idea was developed for clustering using a calculated countenance to discover the ideal number of clusters. At the same time, the CH was selected based on the following three conditions: the residual energy of the node, the dynamic node deployment, and the heterogeneity of the nodes. According to the outcomes of their simulations, utilizing an acoustic communication paradigm instead of an FSO or an EM communication paradigm increased the network longevity the most. This mechanism reduces energy consumption but increases the end-to-end delay.

Hou [28] introduced a layered and clustered UWSN, where the network was divided into layers, with each layer containing one cluster. Its distance from the BS defines the size of a layer, in which closer layers have a lesser thickness than those that are farther away. When "hot spots" appeared, the concept of "layering" was established to manage the transmission between the nodes and the BS. It was determined that the candidate node's residual energy, degree value with neighbors, and distance from the BS were all crucial factors in deciding which one was the CH. The simulation results showed that their framework extended the network's lifetime better than a low-energy adaptive clustering hierarchy (LEACH) and a depth-and-energy-based clustered routing (DEBCR) algorithm.

Goyal et al. [29] proposed a fuzzy clustering algorithm based on the geographic information of the nodes for the cluster formation process and the size of the cluster. They selected the CH based on the following conditions: the distance from the cluster member to the candidate node, the node's distance to the BS, and the energy required for the transmission. The simulation results demonstrated that their proposal decreased the percentage of a node's death better than the LEACH protocol.

Having noted the problems with undersea routing, Ahmen et al. [30] investigated solutions to prolong the battery power of nodes and to control node mobility. Specifically, they recommended the clustered-based energy-efficient routing (CBE2R) protocol, which comprises standard sensor, source, courier, and sink nodes. This system splits the sea depth into seven strata, from the surface to the seabed. The authors also conducted empirical studies to prove these theoretical premises. In particular, they simulated CBE2R performance in contrast to conventional alternatives, such as the energy-efficient routing protocol (DRP), energy-efficient multipath grid-based geographic routing (EMGGR), and reliable and energy-efficient protocol (REEP). Their results prove the superior CBE2R performance, validating it as a solution for efficacious undersea routing. The limitations of the proposed approach are the void area and a fast consumption of courier nodes' energy.

Finally, the authors in [31] employed a clustering technique to partition the network into several layers to resolve the challenge of power consumption in UWSNs using the clustering protocol. In their work, the CH was selected based on the residual energy of the candidate node and the transmission power needed to send data to the BS. The results revealed that their proposal avoided the early death of the distant CHs by routing the packet by multiple hops, rather than sending it directly to the BS. Compared to the Apple filing protocol (AFP) and DEBCR algorithm, the adaptive clustering routing algorithm for underwater acoustic sensor network (ACUN) in [31] consumed less energy overall. The limitation of this approach is that the competition process in CH election requires more message exchange.

Based on the previous paper discussion, we can conclude that the use of cluster-based architecture can help to efficiently build a scalable communication architecture between sensors. It offers the possibility of task sharing over the different nodes and helps to extend the node lifetime.

2.2.3. Detecting Imagery Regarding Underwater Objects

Detecting and classifying sonar imagery concerning underwater objects represents a complicated challenge. High-resolution techniques have been used in several image-processing post-processing approaches to distinguish between the treated objects. Metal can be distinguished from other sub-bottom materials, such as rocks, by using a novel type of unconventional method detecting technique. Padmaja et al. [2] developed an innovative intruder detection system that relies on data mining and machine learning to identify submerged items, with 86% and 90% accuracy for a chosen feature set and a whole feature set, respectively.

It was discovered that deploying autonomous, unmanned vehicles to tow the sonar across the water was more cost-effective than the currently available human techniques. Using acoustic energy transmission at higher frequencies than human hearing, sonar, also known as ultrasonic sensing, is a technology used for obtaining environmental information [1]. Lower expenses, equality of (or higher) performance, and decreased operator deaths and injuries are some of the benefits of using autonomous vehicles, as reported by Khaledi et al. [1]. There were two current sonar alternatives and five distinct towing vehicles examined in the experiment. The underwater vehicle option used the least energy, according to the findings.

All of the available types of background removal are based on the premise that photometric scene characteristics display either temporal stationarity or are static in their behavior. The model fails when used to identify changes in scene dynamics rather than variations in the photometric qualities of the picture, as when trying to detect unusual patterns of automobile or pedestrian activity, for example. The scene dynamics are considered stationary in a new model and computational framework proposed by Jodoin et al. [5]. The method computes events by time-aggregating vector object descriptors with several characteristics. In this study, the researchers devised a novel algorithm that conducted temporal anomaly detection and localization quickly and efficiently. As a result, the current background subtraction approach is able to overcome this shortcoming.

Many factors can affect the classification and detection of underwater objects in sonar imagery, such as the environmental conditions, spatial clutter, the difference in target shapes, the fact that coral reefs may cover targets, and other factors. To cope with these challenges, the authors in [32] proposed a new method for detecting and classifying underwater objects in sonar imagery using canonical correlation analysis (CCA). CCA is efficient in extracting coherent features to enhance the classification and detection process, can distinguish between the return from the bottom of the water and objects, and can detect the activity of the target. Ultimately, CCA proves efficient in classifying and detecting underwater objects in sonar imagery and can reduce the false alarm rate.

The authors in [33] proposed a new algorithm for detecting submerged objects using synthetic aperture sonar (SAS). The algorithm merges highlight and shadow detection based on a weighted likelihood ratio test. The scheme's primary advantage is detecting targets without any knowledge about their size or shape. Then, it uses a support vector machine (SVM) classifier to extract the statistical features of the pixels to detect the shadow in the regions of interest (ROIs). Finally, the authors proved the robustness of the proposed approach by comparing it with existing approaches.

One of the most significant UWSN technologies is localization, which is critical because it is employed in many applications. In Ref. [6], the authors classified localization algorithms into three categories according to the mobility of the sensor nodes, as follows: mobile localization algorithms, stationary localization algorithms, and hybrid localization algorithms. The detailed comparison of these localization algorithms has revealed existing knowledge gaps, such as the localization algorithms for hybrid and mobile UWSNs, which could lay the foundation for further research in this domain.

AI techniques were also used by Guo et al. in [34] for the detection, quantification, and visualization of dense microcracks in HPFRCC using a limited dataset of images with high-accuracy CNN-based model classification. This work shows the importance of using AI detection techniques for accurate classification. This statement was also confirmed by Liu et al. in [35], where the authors have shown the efficiency of applying machine learning algorithms for the efficient detection of anomalies.

Using image-based sensing for underwater object detection requires high energy consumption in the processing of data for feature extraction and classification. We believe that, in our case, the use of the underwater sonar sensing approach will be more appropriate for efficient, low-energy cost classification.

2.2.4. Energy Resource Management in UWSNs

Void node avoidance algorithms represent a crucial strategy for energy-efficient resource management in the energy-constrained UWSNs. Javaid et al., in [8], proposed AVN-AHH-VBF and CoAVN-AHH-VBF as two different UWSN routing protocols, with one based on collaboration (CoAVN-AHH) and the other based on ad hoc vector-based adaptability (VBA). Both models employed sensor nodes to forward data packets, but the strategies used to keep the network from flooding differed in each model [8]. However, compared to the existing void node avoidance methods, these suggested methodologies significantly improved the network performance. The limitation of this proposed approach is that it is not flexible enough when the nodes follow an irregular distribution.

To optimize the available resources and prolong the network lifespan, Sher et al. [36] proposed the following four systems: collision-avoidance-based WDFAD-DBR (CA-DBR), backward-transmission-based WDFAD-DBR (B-DBR), cluster-based WDFAD-DBR (C-DBR), and WDFAD- depth-based routing (DBR) and (A-BDR). The C-DBR creates small groups of nodes to collect data, limiting the end-to-end delay. Contrarily, the A-DBR averts void nodes by altering the transmission range adaptively. The B-DBR finds an alternative data packet route delivery, while the CA-DBR minimizes collision. Simulations of the four systems display superiority to the baseline alternatives regarding the accrued propagation distance, end-to-end delay, energy tax, and average packet delivery ratio. In brief, jointly deploying the four schemes facilitates void hole avoidance, enabling reliable data transfer. The limitations of the DBR approach are void holes, increased energy consumption, and high end-to-end delay.

Considering the need for efficient packet transmission, Chaaf et al. [37] proposed the relay-based void hole prevention and repair protocol (ReVOHPR). This strategy is highly effective for locating and avoiding trap relay nodes and void holes. In addition, the protocol employs several cutting-edge technologies to make sure that it works even while submerged. It is easier to transport traffic between clusters when there are as many matching nodes as possible. Bi-criteria mayfly optimization may also locate and fix void holes in a given structure, which is an added benefit. The authors also simulated ReVOHPR's performance and found that it outperformed the baseline traditional approaches by a wide margin. Because of this, the void hole issue is no longer a concern when using ReVOHPR. Void holes still exist and are an overhead, due to control packets' exchange.

The huge size and restricted communication radius characterize a wireless sensor network. The effective delivery of a data packet and a pattern of nodes is largely dependent on multi-hop transmissions [13]. While approximating the forwarding multi-hop paths quality is imperative, existing metrics, for instance, ETX, overlook the forwarding capabilities inside the sensor nodes and concentrate on gauging the link performance between the nodes. The researchers in [13] proposed quality of forwarding (QoF) to fill the knowledge gap left by previous studies. QoF assesses the performance in the gray zone inside a node, and the measurements of the intact path quality support the designing of efficient multi-hop routing protocols. The study outcomes have revealed that the developed modified collection tree protocol considered both forwarding reliability and transmission cost, resulting in high throughput for data collection.

Additionally, Ismail and Bchir [16] proposed a new approach for automatic mine detection in sonar data, which relies on a possibilistic-based fusion technique to categorize sonar incidents as mine-like or mine objects. This approach produced optimal fusion parameters for every setting, and the outcomes proved that it outperformed unsupervised local fusion and individual classifiers.

Finally, the literature analysis shows how far UWSN development has come in the last several years. Researchers have presented feasible solutions for several challenges, including void holes, the limited availability of battery power, and uncontrolled node mobility. However, the techniques shown here are an excellent starting point for creating an energy-aware framework for detecting underwater mines.

3. UWASN Energy Consumption Model

In recent years, target detection has gained attention from researchers. Many existing detection mechanisms have been proposed to detect underwater mines with high accuracy using WANs. However, processing acoustic signals consumes more energy, directly affecting the network lifetime. Energy consumption is one of the primary issues in sensor networks, due to the inability to replace or recharge their batteries. Furthermore, each sensor node has significant power constraints, and the amount of energy consumed will impact both the network performance and the lifetime of the sensors.

The network contains many acoustic sensor nodes and sink nodes that are placed and distributed over the area of interest to monitor the surrounding environment by sending acoustic signals. The network is partitioned into clusters, each containing a CH and several member nodes. Instead of sending the raw sensor node data to the CH, each member sensor node is responsible for sensing the surrounding environment, processing the received signals, and extracting the features from them. When an event of interest occurs, the sensor nodes extract the features from the acoustic signal and use them to identify the type of detected object using the classification algorithms. Then, the sensors send the packets to their CH. After that, the CH applies the classification process to classify the detected object. Once the CH detects a mine, it transmits the target's detection information to the BS. Since each sensor extracts features from the signal, and the CH applies a classification process to classify the detected object, the size of the transmitted packet sent to the BS is reduced, leading to decreased energy consumption for communication within the network. The communication process consumes more energy compared to signal processing. When we reduce the size of the transmitted packets, we preserve energy, which leads to an increased network lifetime.

Furthermore, it is important to use a classification algorithm that can accurately classify the detected object using the extracted features and with a high accuracy rate. This helps to reduce the memory space overhead. Since the energy consumption of the sensor nodes is directly affected by the computational complexity of the adopted algorithms, the energy consumption increases during data processing. Therefore, it is essential to use low-complexity algorithms that can accurately classify the objects using fewer instructions.

The UWASN energy model is based on the dissipation of the acoustic energy used in [14] to produce it. The compression and dilation of a medium result in the generation of acoustic waves when a mechanical disturbance occurs. The propagation medium's elasticity is a characteristic of this phenomenon [6].

$$SL = TL + 85 \tag{1}$$

where TL is the transmission loss and SL is the source level. The purpose of SL is to calculate the amount of sound radiated by a sound source. It refers to the intensity of the radiated sound at a distance of 1 m from the source. Furthermore, the intensity indicates the amount of sound power transmitted through a unit area in a particular direction. The source level is the relative intensity and uses decibel (dB) units. The decibels units are used in underwater sound, and the (dB) is measured as a pressure of 1 microscale (μPa). All of the parameters in Equation (1) are in dB re μPa, and the value of 1 μPa is equal to 0.67×10^{-22}. Different signal shapes have different transmission losses. When transmitting a cylindrical signal, the transmission loss is as follows:

$$\alpha\hat{} = \begin{cases} 0.0601 \times f^{0.8552} & 1 \leq f \leq 6 \\ 9.7888 \times f^{1.7885} \times 10^{-3} & 7 \leq f \leq 20 \\ 0.3026 \times f - 3.7933 & 21 \leq f \leq 35 \\ 0.504 \times f - 11.2 & 36 \leq f \leq 50 \end{cases} \tag{2}$$

The required threshold value of α, indicated by α^, must be larger than that of α^ to obtain a better reception. However, α^ is a monotonically decreasing function of frequency f. For convenience, we consider α^ to be α^(f), hereafter. The essential transmitter power P_t to obtain intensity I_t at a distance of 1 m is as follows:

$$P_t \ = 2\pi \times 1m \times H \times \ I_t \tag{3}$$

where I_t is defined in terms of SL as follows:

$$I_t \ = 10^{\frac{SL}{10}} \times 0.67 \times 10^{-18} \tag{4}$$

Finally, P_t is represented as follows:

$$P_t \ = ZHde^{a(f)\mathrm{d}} \tag{5}$$

where $z \simeq 2\pi(0.67)10^{-9.5}$, $a(f) \simeq 0.001\alpha(f)ln10$, and H is the water depth in meters.

With the transmission of l bits over distance d, the dissipated transmission energy can be expressed as follows:

$$E_{TX}(l,d) = lE^T_{elect} + lT_b ZHd_{toCH}e^{a(f)d_{toCH}} \tag{6}$$

and the receiver radio energy consumption can be expressed as follows:

$$E_{RX}(l,d) = lE^R_{elect} \tag{7}$$

where E^T_{elect} and lE^R_{elect} are the energy consumed by the transmitter and receiver to process the l bits of data, respectively, and T_b is the bit duration in seconds.

4. Proposed Work

The proposed approach consists of two phases. In Phase 1, we start at the edge to determine the required extracted features. Then, we deploy these features to the sensors. In Phase 2, the sensors sense the surrounding environment in order to detect the mines. When a mine is detected, they extract the features and send packets to their CH. The CH performs the classification and sends the notification packets to the BS if the detected object is a mine. Finally, the CH assigns weights to all of the features received from its cluster members based on the signal strength. After a certain period, the edge can send an improved list of required extracted features to the sensors.

The main contribution of this paper is the design of a scheme that focuses on decreasing the complexity of the object detection process in the UWASN and the enhancement the classification process. In order to achieve this goal, an appropriate algorithm for feature extraction and classification must be applied [38]. The following two significant factors are necessary to accomplish this task:

1. The constraints of network resources, such as a small memory size, limited power supplies, and low communication, are the main characteristics of WSNs. Therefore, it is essential to use a model that can make recognition decisions with a minimum number of datasets.
2. The computational complexity is another critical factor. The feature extraction and classification process at the sensor level increase the energy consumption. However, the amount of transmitted data will be decreased [38].

The goal of this research is to develop an efficient method for detecting and disarming underwater mines and related substances in various marine environments by using underwater acoustic sensors with wavelet transform (WT). This system will provide accurate and reliable information on the location of underwater mines and related substances. The use of underwater sensor networks (UWSNs) will enable the gathering of all of the necessary information under different circumstances, facilitating the identification and clearance of underwater minefields and promoting disturbance-free aquatic life. This approach will ensure that different marine life and related activities can enjoy disturbance-free aquatic life, as unexpected blasts that destroy aquatic life and degrade the marine environment, which may even be eradicated. The proposed work will involve several stages and models working together to provide accurate information on the location of underwater mines. The first step is to extract the features from the sonar signal to distinguish mines from other mine-like objects underwater, and the second step is to deliver a notification when a mine is detected.

4.1. Network Model

There are three main types of transmission mediums for underwater communication: radio wave communication (electromagnetic), optical communication (light), and acoustic communication (sound). However, radio and optical communication are inefficient underwater, due to poor performance, leaving acoustic communication as the primary option, due to its low attenuation in water [39].

Acoustic communication involves using sound signals for communication between the sensors in the network. These signals can transmit over long distances, compared to electromagnetic and optical waves, making them ideal for underwater communication. Underwater acoustic sensor networks (UASNs) consist of numerous sensors that use acoustic signals to communicate for various underwater applications, such as monitoring risks. Each sensor sends an acoustic wave and receives the reflexion of the objects. The received acoustic signal will be processed, and the extracted features will be transmitted to the cluster head (CH), which then processes it along with other possible notifications coming from the other sensors in the same cluster. The CH will be in charge, using these signals to detect mines using an ML-based classifier. The underwater sensor nodes communicate with their respective cluster heads (CHs) using acoustic signals to transmit packets [40]. The density of the nodes impacts the detection accuracy of mines. In depth, if we increase the nodes' density, the distance between the mines and the acoustic sensor decreases, which provides better received signal power. Furthermore, a higher number of sensors will report the detection of a mine to the cluster head, which gives more available data to the cluster head in order to accurately classify the detected object.

Acoustic sensor nodes are placed underwater and organized into multiple clusters. One CH in the cluster collects the sensor node packets and transfers them to the BS over acoustic signals. It is easy to see why the BS is located near to the shore, close to the water. The BS obtains the packets from the CHs submerged underwater and then directs them through radio frequency transmission to the on-land controller using RF communication. Figure 2 illustrates the network model used in this work.

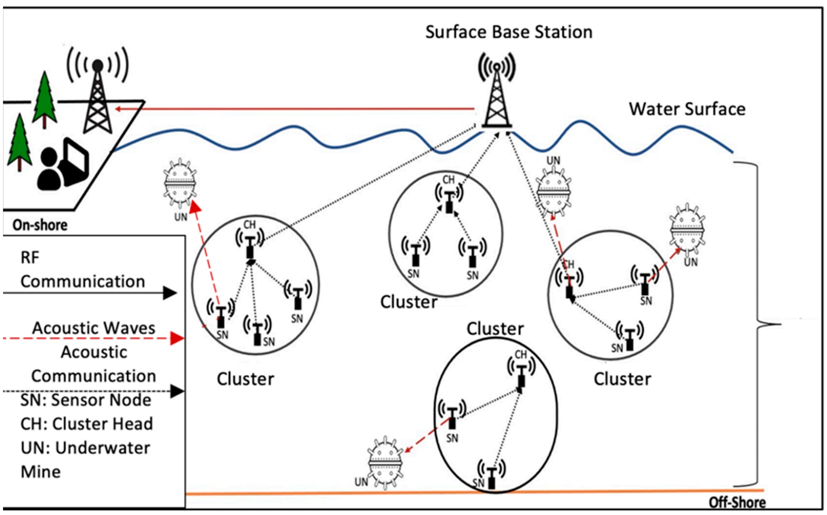

Figure 2. Network model.

4.2. Detection Scheme at the Sensor Node

The acoustic sensor node continuously senses the surrounding environment by sending acoustic signals underwater and receiving signals from the underwater objects. When the sensors receive signals, they process them using WT to extract their features. Then, they transmit these packets to their CH in order to complete the classification process to detect the type of detected object. After that, if the detected object is mine, the CH will send the notification packet to the BS. The detection scheme is presented in Figure 3.

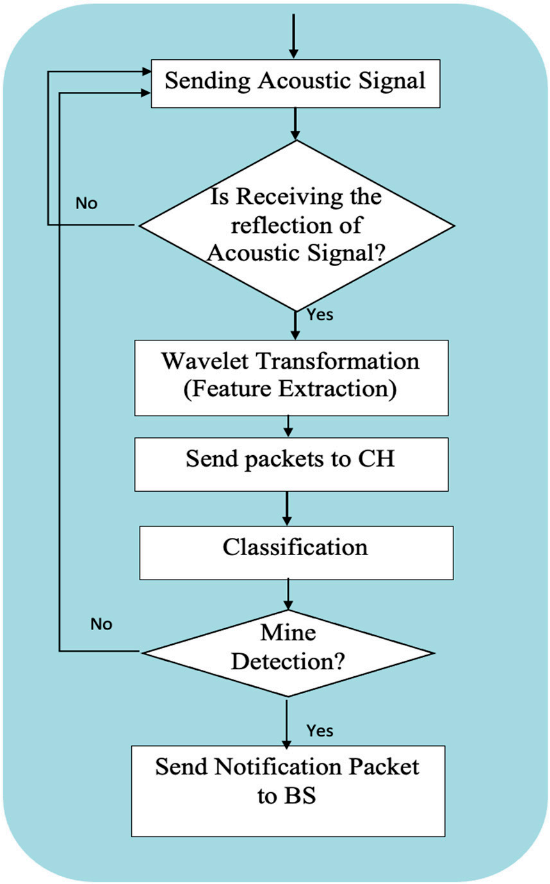

Figure 3. Flowchart of general scheme for the object detection process.

4.3. Feature Extraction Using Wavelet Transformation

WT is a time- and frequency-domain method that is used to extract significance and reveal hidden information from the original signal. It analyzes the signal at different levels and resolutions, thereby extracting more relevant information [41]. It is widely used to detect inter alia, heart rates, and specific objects. It can apply both continuous wavelet transformation (CWT) and digital wavelet transformation (DWT). CWT is defined as follows:

$$W_{\psi} f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi\left(\frac{t-b}{a}\right) dt \tag{8}$$

where $f(t)$ is a signal, $\psi(t)$ is a mother signal, a is the dilatation, and b is a translation. CWT is not randomly used for predictions, because it is computationally difficult and time consuming [42], and the creation of redundant factors to a substantial volume of computation [43]. DWT transformation is defined as follows:

$$W_{\psi} f(2^c, d2^c) = \frac{1}{\sqrt{2^c}} \int_{-\infty}^{\infty} f(t) \psi\left(\frac{t-d2^c}{2^c}\right) dt \tag{9}$$

where c is the scale and d is the translation variation. DWT is often used because it requires less computation time and is simpler to apply. Furthermore, DWT is more suitable for time-critical applications or situations where the power supply is limited [44]. For these reasons, DWT is an effective selection for sonar signal processing. Different wavelet families implement DWT, and they have unique features. These families include Haar, Morlet, complex Morlet, Meier, Daubechies, Coiflets, and Shannon–Kotelnikov. The Haar wavelet family is preferred over the other families because it is simple and sufficiently resolves various problems [43]. In addition, Haar has a high computation speed and is memory-efficient. Also, it does not require extra memory for its calculations [45]. Since the principal aims of this work are to deal with limited computational capability and reduce the energy use, the Haar wavelet was chosen as the function to transform the sonar signals and extract the features. Furthermore, implementing the Haar wavelet increases the classifying ability to distinguish mines from other objects, because it extracts only the crucial features from the signals.

Discrete wavelet transformation (DWT) is a widely used technique for feature extraction, due to its efficiency in this area. Previous studies have demonstrated that using this technique can produce good results. The primary goal of this feature extraction method is to reduce the dimensionality by removing the irrelevant features and selecting the optimal group of attributes from the original data [46]. Furthermore, this feature extraction method can reduce the time needed for training and processing data and improve the accuracy by using DWT to remove the redundant features and clean the data.

4.4. Classification and Mine Detection

After the transformation of the signal, a high level of accuracy is required for the classification. Misclassified mines could lead to explosions, rendering the detection system useless. In order to enable the classification at the sensor level, a classifier must possess the following characteristics:

First, the classifier must have a high accuracy in classifying mines and related substances, with a low misclassification rate. Second, it should have a low computational complexity, as the energy consumption of the sensor node is directly affected by the computational complexity of the classifier. Third, it should have a small memory footprint, as the sensor node has limited memory resources. Finally, it should be able to handle the non-stationary nature of the underwater environment, as the acoustic signal characteristics can change over time.

The Naïve Bayes classifier is a probabilistic classifier based on the Bayes rule theorem, which assumes the attribute $X = X_1, \ldots, X_n$ is fully independent of a given output class Y. This is called the conditional independence assumption [47]. Considering that X contains n attributes, its representation is given by [48], as follows:

$$P\frac{(X_1,\ \ldots,\ X_n)}{Y} = \prod_{i=1}^{n} P\left(\frac{X_i}{Y}\right) \tag{10}$$

A supervised classifier is used to classify the data in order to make predictions about the outcomes [49]. Compared to the other classifiers, Naïve Bayes is efficient because it uses a simple calculation, requires less computational complexity and memory, and has high accuracy [50]. Given these advantages, we selected the Naïve Bayes classifier to discriminate the mines from the other objects.

The clustered protocol proposed in this work is based on the protocol presented in [14]. The network includes multiple sensors that use a transmission medium to perform distributed sensing. The main idea here was to compare the performance of the cluster protocol using the following three different transmission media: acoustic, free-space optics (FSO), and electromagnetic (EM). The findings of the protocol were as follows [14]:

- In a Gaussian-distributed underwater sensor network (UWSN), acoustic waves outperform free-space optics (FSO) and electromagnetic (EM) communication techniques in terms of the optimal number of clusters.
- Therefore, for any underwater application using a clustering topology, acoustic communication requires less energy.
- However, acoustic underwater communication is limited by the bandwidth, and the behavior of optimal clustering is not uniform across the bandwidth. The best number of clusters can be achieved at the lower bound of the bandwidth.

Acoustic waves are, thus, the least lossy underwater, as they support long-range signal transmission. Moreover, they are mainly employed in underwater communication. Acoustic communication is bringing back this once-defunct underwater communication mechanism.

In their work, the distribution of the sensors uses a mathematical formula to achieve an optimal number of clusters. The aim is to overcome the issue of using too much energy because of the increased overall communication overhead if the distribution is based on having more clusters while distributing the sensors equally on each cluster [14]. However, fewer clusters use more energy to transmit the data from the CH to the BS. The ideal number of clusters by means of the acoustic waves is defined by the following formula [14]:

$$(K_{opt})_{Acoustic} = \sqrt{\frac{\left(\frac{N}{6}\right) a(f) T_b Z H M^2}{T_b Z H (d_{toBS} + a(f) d^2{}_{toBS}) - \frac{M^2}{12} T_b Z H - E^R_{elect}}} \quad (11)$$

where N is the number of nodes, $a(f)$ is the absorption coefficient, T_b is the bit duration, Z is a constant, H represents the sea depth, M is the length, E^R_{elect} is the energy dissipation in the electrical circuit, and d is the distance between the transmitter and the receiver in meters.

The optimal number of clusters depends on the dimensions of the sensing field (M), the number of sensor nodes (N), the distance between the nodes and the BS (d_{toBS}), and the energy consumption of the transmitter electronics (E^R_{elect}). Consequently, the optimal number of clusters is independent of the energy consumption of the transmitter electronics.

Using the optimal number of clusters as a guide, the sensor nodes can self-organize into clusters using distance-based segmentation to group themselves in a decentralized manner. This method outperforms the low-energy adaptive clustering hierarchy (LEACH) protocol in resolving energy imbalances. These imbalances usually occur in the LEACH when it does not consider sensing coverage and distance from the base station (BS) in selecting the cluster heads (CHs). The CHs are selected by using the distribution formula, which is calculated in each node. The selected nodes then send their self-selection decision to the other sensor nodes in the network, and the other nodes then organize themselves into clusters after the most suitable CH is selected from the self-elected nodes. Therefore, the CHs use time-division multiple-access (TDMA) methods to send packets from the sensor nodes to the BS.

5. Sensing Methods

The sensors used in the UWSNs can operate in different modes and methods depending on the circumstances and environment deep underwater. In underwater acoustic sensing systems, the sensors operate in the following three different modes: 2D, 3D, and hybrid [51]. These modes function differently to detect and provide data on substances underwater.

- 2D

In a two-dimensional (2D) environment, static sensor nodes are typically installed in submerged positions on the seabed. These nodes connect with a sink node for data transfer via multi-hop communication across multiple clusters [51].

- 3D

In a three-dimensional (3D) design using inflated buoys as supports, sensors are deployed at different depths by modifying the length of the cable that connects to the anchor on the sea bottom [51]. The sensor nodes in the mobile architecture have the freedom to move around. This allows for the dynamic reconfiguration of the network topology. In the mobile architecture, the sensor nodes have the freedom to move around, allowing for the dynamic reconfiguration of the network topology. The mobile nodes require two transceivers for proper functioning. To enhance the network capabilities and gather data, remotely operated underwater vehicles (ROVs), autonomous underwater vehicles (AUVs), or sea gliders can be used. A hybrid design is a third type of vehicle, which mixes static and mobile sensor nodes to fulfill specific functions [42]. Mobile nodes can operate as routers or controllers in a hybrid vehicle to connect with static or standard sensors in a distributed system for data sensing [51].

Past research has shown that acoustic communication is suitable for underwater communication. Acoustic signals can travel long distances underwater, and the communication range between the nodes is large, allowing for sparsely dispersed underwater acoustic sensors. This kind of deployment is suitable for many applications, such as pollution and habitat monitoring, where the loss of some data is acceptable to a certain extent [52]. However, for critical applications that involve critical data, such as intruder detection and mine detection, a dense deployment of nodes is necessary and required. In such cases, losing even the slightest amount of data is not acceptable [53].

6. Implementation and Simulation Environment

The dataset used in this work was obtained from the UCI Machine Learning Repository and is called the connectionist bench sonar dataset, which includes the mines vs. mocks dataset [54]. This task trains the network to define the type of sonar signal reflected off a metal cylinder or cylindrical rock. This dataset contains two types of files. The first file is "sonar. mines," which consists of 111 patterns acquired from bouncing signals off a metal cylinder at various angles and under different circumstances and labeled "M". The second file is "sonar. rocks," with 97 patterns of signals that bounced off rocks under similar conditions and was labeled with "R.".

The sonar transmitted is a frequency-modulated acoustic chirp, where the frequency increases over time. A chirp is a signal containing a frequency that increases or decreases over time. The signals are transmitted at various angles, covering 180 degrees for the rocks and 90 degrees for the metal cylinder. Each pattern contains 60 decimal numbers, with values between 0 and 1 representing the attributes or features of the bounced signal. Each attribute represents the amount of energy within a particular frequency band.

For the evaluation process, we have used 70% of the data for training and 30% of the data for testing. We used the Python programming language and NS-3 simulation environments to measure the different metrics of the work. We employed the following metrics to evaluate the proposed work's mine detection scheme and network performance (Table 1 lists the simulation environment parameters). We have selected a square area of 50 m × 50 m, with a depth of 50 m. In this area, we deployed a variable number of nodes that ranged from 1 to 100, with a base station located in the center. The packet size was composed of 500 bytes, which were used for the exchange of data between the different nodes.

Table 1. Simulation environment parameters.

Parameter	Description
Sensing field	Square-shaped
Base station location	Center
Dimensions of the sensing field	M × M
M × M	50 × 50 m^2
Sea Depth (H)	100 m
E^{T}_{elect}	50 nJ/bit
E^{R}_{elect}	50 nJ/bit
L	500 Byte
Number of nodes	1–100
Packet size	500 bytes

- *Accuracy:* The number of correct predictions by the classifier divided by the total number of predictions.

$$Accurcy = \frac{TP + TN}{TP + TN + FP + FN}$$

where *TP* and *TN* represent the number of true positive and true negative predictions, respectively, and *FP* and *FN* represent the number of false positive and false negative predictions, respectively.

- *Mean absolute error*: The mean of the absolute values of the individual prediction errors for all instances (n) in the test set. Each prediction error is the difference between the true θ_i and the predicted values of $\hat{\theta}_i$ for the instance.

$$MAE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}\left|\hat{\theta}_i - \theta_i\right|$$

- *Root mean squared error*: The square root of the average of the squared differences between the prediction and the actual value.

$$RMSE = \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}\left(\hat{\theta}_i - \theta_i\right)^2}$$

- *Kappa statistic*: The statistic used to test the interrater reliability.

$$Kappa = \frac{observed\ accuracy + expected\ accuracy}{1 - expected\ accuracy}$$

- *Root relative squared error*: The value used to measure the difference between the predicted and the observed values of the instance, where n is the number of all instances.

$$RRSE = \sqrt{\frac{\sum_{i=1}^{n}\left(\hat{\theta}_i - \theta_i\right)^2}{\sum_{i=1}^{n}\left(\overline{\hat{\theta}_i} - \theta_i\right)^2}}$$

- *Throughput*: The rate at which the packets are successfully transmitted between the sources and the destinations in the network, measured in packets per second.
- *Packet delivery ratio (PDR)*: The ratio of packets transmitted to the number successfully delivered in the network.
- *Network delay*: The end-to-end delay in the transmission process, measured as the mean time from when the source sends a packet to when the message is successfully received at the intended destination.
- *Average energy consumption* vs. *the number of rounds*: The average remaining energy in the nodes at a specific round.
- *Alive nodes*: The number of nodes that are alive at a specific round.

7. Results and Discussion

To evaluate the accuracy of the proposed method during the analysis stage, experiments were performed using different classification algorithms, including support vector machines (SVMs), random tree, J48, and K-star. Picking one algorithm could lead to limited results. Also, in order to save time and cost, we could not try every algorithm. We selected a group of popular algorithms in the literature that belong to different families of ML algorithms (numerical, symbolic, etc.)

Table 2 shows the outcomes obtained from using these algorithms. Additionally, Figure 4 illustrates the distribution of data points belonging to the two classes (mines in blue and rocks in red) after applying the Level 3 Haar function to the dataset. This shows a clear grouping of each class after feature extraction, thereby enhancing the classification accuracy.

Table 2. Comparison of classifiers.

Classifier	Fivefold CV	Tenfold CV	50%–50% Training–Testing
Naïve Bayes	95.1691%	94.686%	93.2039%
SVM	92.7536%	91.3043%	93.2039%
K-star	74.3961%	75.8454%	65.0485%
J48	89.8551%	88.8889%	79.6117%
OneRule	88.4058%	89.372%	91.262%
Random Tree	83.0918%	87.9227%	85.4369%
LMT	91.7874%	91.3043%	92.233%

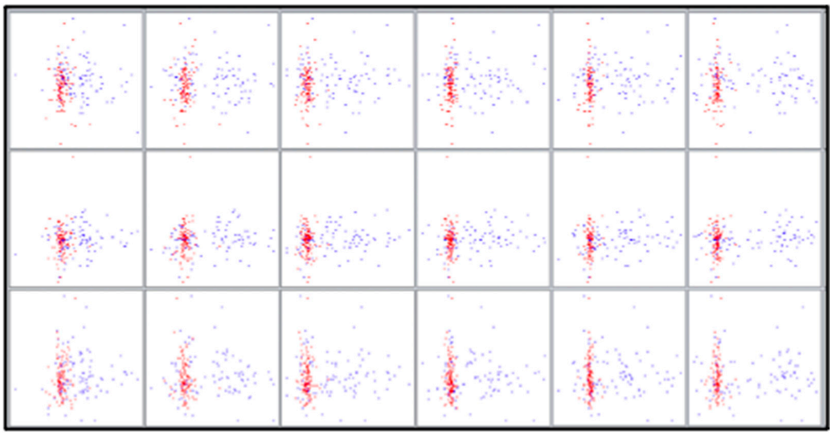

Figure 4. Data distribution after applying WT.

This result can be explained by the fact that Haar wavelet transform provides details and high resolution in the time-frequency domain of the processed acoustic signal, which helps to extract the relevant features that will be efficiently used in the classification. The wavelet transform applied to the different levels allows us to extract the different frequency sub-bands that comprise the signal and has high adequacy in classifying the object accurately.

The results have shown that the Naïve Bayes classifier achieved the highest accuracy (95.1691%) when using the selected dataset in both the sevenfold and the fivefold cross-validation, outperforming the other classifiers. The random tree classifier produced similar results to Naïve Bayes, but Naïve Bayes was lighter and simpler, making it more suitable for practical applications. Table 3 presents detailed results of the selected classifier, successfully classifying 197 out of 207 objects and incorrectly classifying only 10 objects, with a low mean absolute error (MAE) of 0.0473. Additionally, a comparison of the fivefold and tenfold classifications is shown in the table.

Table 3. Naïve Bayes classification results.

Accuracy (%)	Correctly Classified Instance	Incorrectly Classified Instance	Kappa Statistics	MAE	RMSE	RAE
95.12%	197	10	0.90	0.0473	0.21	9.50%

Table 4 compares this study with the previous efforts carried out on the same dataset. Three other researchers used wavelet transform (WT) in their studies, while four used different techniques. As the table indicates, the proposed method yielded better results than all of the previously used methods. While the accuracy of the three studies that utilized a comparable methodology (wavelet) varied between 80% and 94%, the proposed method achieved a classification accuracy of 95.1691%. The four other studies yielded accuracies of between 72% and 89%. This suggests that WT improves the classification accuracy. Therefore, the proposed study's higher accuracy compared to all of the previous studies indicates a significant contribution to this field.

Table 4. Comparison of other works.

Work	Accuracy (%)	Method
Bakbak et al. [21]	94.23 (tenfold CV) 95.19 (50% training–testing)	Wavelet transformation methods
Libal et al. [22]	88	
Battula et al. [23]	82.82	
Proposed work	95.1691 fivefold CV) 93.2039 (50% training–testing)	
Chatterjee and Raghavan [50]	94.23 (tenfold CV) 95.19 (50% training–testing)	Other data preprocessing methods
Jiang [55]	82.19 tenfold CV	
Jiang et al. [56]	83.64 fivefold CV	
Kheradpisheh et al. [57]	72.34 fivefold CV	

Figure 5 illustrates the amount of energy consumed by specific numbers of nodes in the proposed work. It shows that energy consumption is logically proportionate to the detection scheme at the sensor node. Since the detection steps include signal transformation followed by the classification, the energy consumption result is reasonable. Each time an object was spotted, these procedures were carried out. We also employed an optimum clustering method to decrease the energy consumption, since the node's residual energy plays a role in picking the CH. Compared to the work in [29], the proposed work consumed less energy in the former work; furthermore, the amount of consumed energy ranged from 210.28960 joule to 214.57170 joule, depending on the packet size (packet size: 50, 100, 150, 200, and 250 bytes). Moreover, even when the packet size in [29] was smaller than the packet size in the proposed work herein (packet size: 500 bytes), the energy consumption in [29] was still higher. The chart in Figure 5 compares the proposed work and the previous protocols used in [37] in the aspect of consumed energy. The proposed work provided a reasonable consumption of energy with 10 nodes, in comparison to the ReVOHPR protocol. However, when the number of nodes increased to 25, the energy consumption increased, but the proposed work still provided well in terms of energy consumption in comparison to the rest of other protocols. Until the number of nodes reached 100, the proposed work consumed less energy, only in the comparison to the PSO protocol. Figure 6 shows that the proposed work consumed less energy than all of the protocols presented in [30]. Overall, the outcomes of the suggested work look positive in terms of consumed energy.

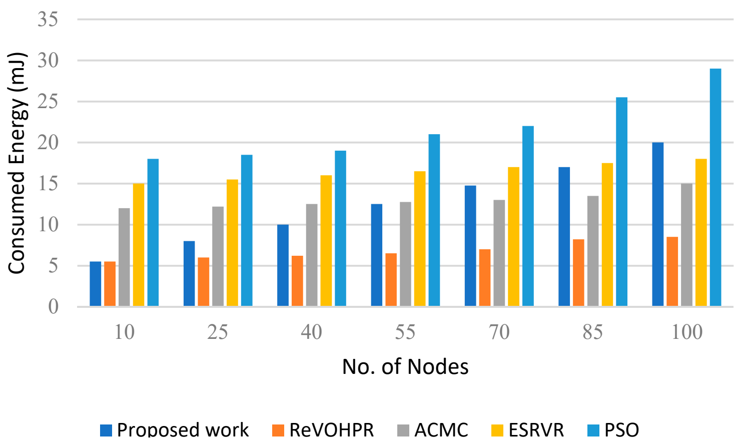

Figure 5. Energy consumption results compared with protocols in [37].

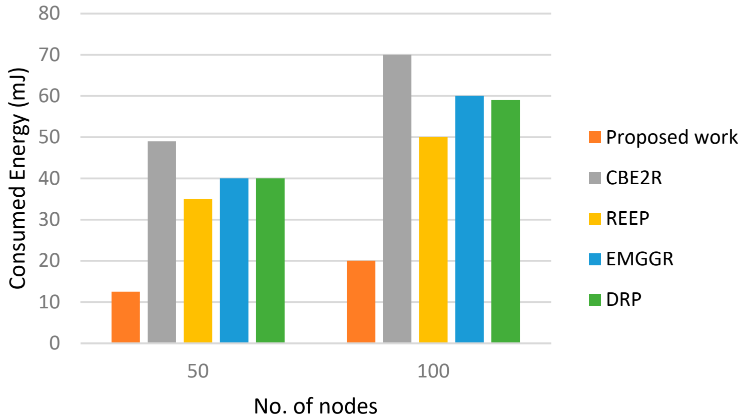

Figure 6. Energy consumption results compared with protocols in [30].

Figure 7 illustrates the network delay in relation to the number of nodes. As the number of nodes increases, the delay increases, because the CHs receive more packets from the sensor nodes. The comparison of the proposed work with the other protocols from [37] shows that the proposed work had less delay time than all of the other protocols with varying numbers of nodes. Furthermore, the proposed work provided less delay in comparison to all of the protocols provided in [36]. When the number of nodes was 100, the least delay achieved was 6.8 s, by the CA-DBR protocol, which is more than the proposed work. Figure 8 shows a comparison between the proposed work's delay and the protocol delay provided in [30]. The proposed work has less delay in comparison to the other protocols.

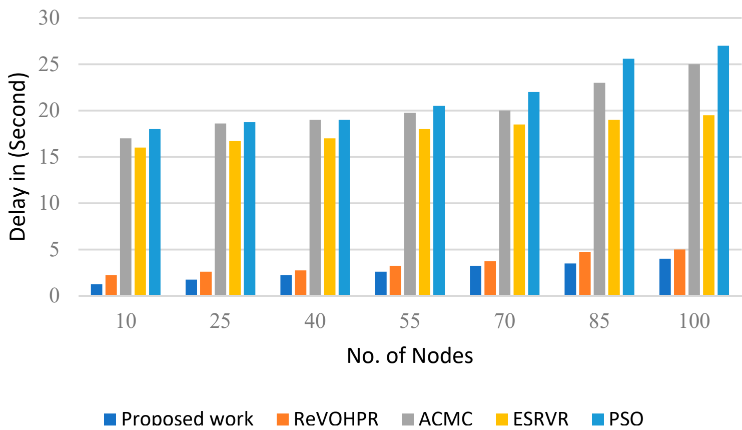

Figure 7. Delay results compared with protocols in [37].

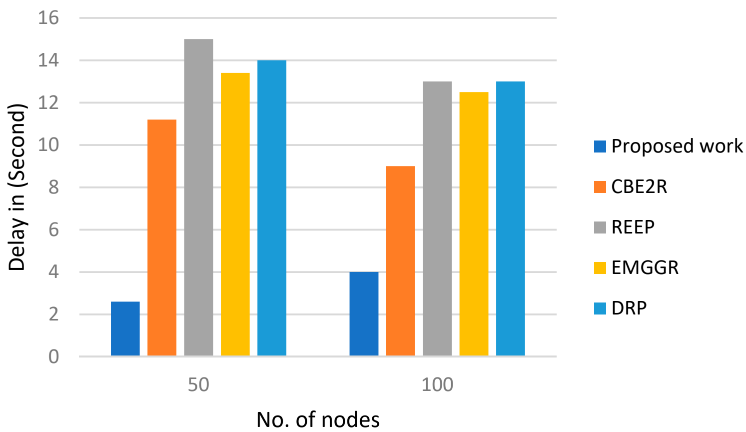

Figure 8. Delay results compared with protocols in [30].

Compared to the previous study [29], the PDR was more significant in the suggested work, with a PDR of 67% for 100 nodes. More importantly, with 100 nodes, the highest PDR value was 80% in the work of [27], which is lower than the figure reported in the proposed study. Furthermore, in [36], all of the protocols produced a lower PDR, with the CA-DBR protocol providing the highest percentage at 78% at 100 nodes. Figure 9 illustrates a comparison between the proposed work and the previous procedures [37]. Exceptionally, the suggested work produced better results in comparison, except in contrast to the ReVOHPR protocol, which was 96% at 100 nodes compared to 90% for the proposed work. Figure 10 provides a comparison between the proposed work and the protocols provided in [30]. The proposed work provided a higher PDR than the protocols, with the same number of nodes. On the other hand, Figure 11 shows that, when the number of sensor nodes rises, the throughput standards upsurge along with them, and the transmission rate in the network also increases. The high throughput attests to the capability of this approach to support the intensive exchange between the nodes of the cluster participating in the detection of the acoustic signal and the classification. It also shows that the network allows us to exchange high frequency of notifications with the sink node submitted by multiple cluster heads. In comparing the throughput of the proposed work to that of the protocols in [37], it can be seen from the graph that the proposed work provided lower throughput values in general in comparison to the other protocols. Also, when the proposed work was compared to the protocols in [30], the protocols adopted achieved a better throughput.

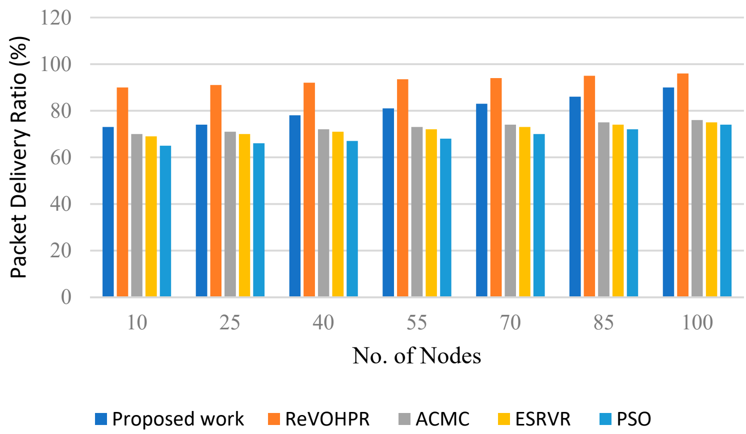

Figure 9. Packet delivery ratio results compared with protocols in [37].

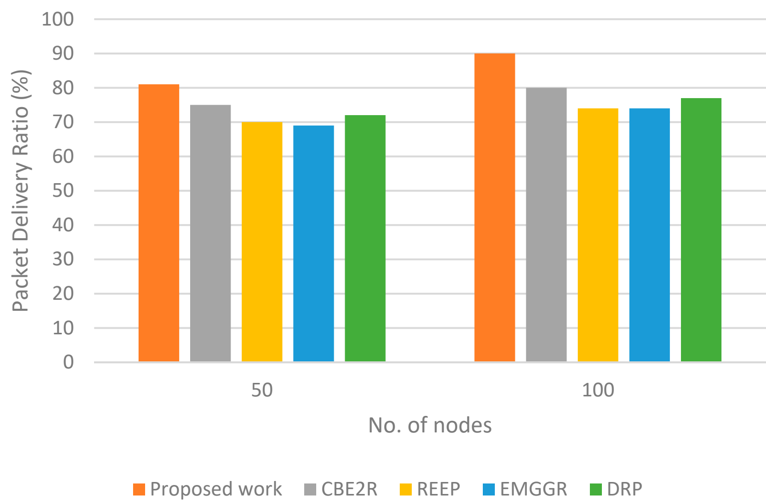

Figure 10. Packet delivery ratio results compared with protocols from [30].

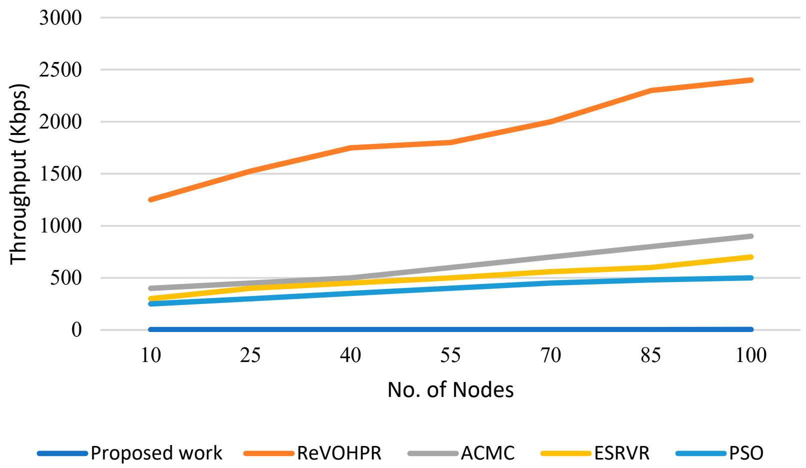

Figure 11. Throughput results and comparison with protocols from [37].

In Figure 12, the number of alive nodes declines from 100, and more than half are still alive after 300 rounds. Hence, the proposed work must exceed 900 rounds before all of the nodes are dead. By comparison, Ref. [28] and Ref. [31] reached the end in the 800th and 500th rounds, respectively. Therefore, even though their nodes' energy consumption was less than that of the proposed work, our proposed method of conserving energy by applying optimal clustering is better for extending the network's lifetime.

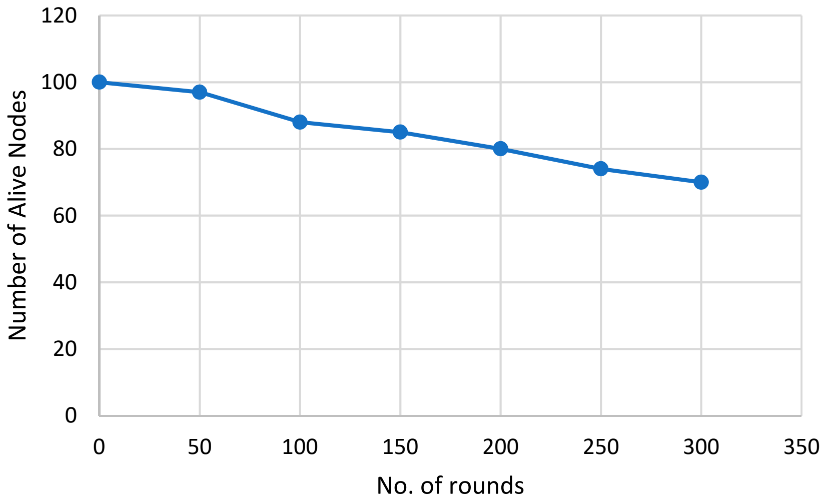

Figure 12. Alive node results.

8. Conclusions

A UWASN system is designed to continuously observe the underwater environment for environmental and critical applications. When used in critical systems, UWASNs can serve as a submerged mine detecting network that enhances the recognition procedure while being a harmless alternative. However, each sensor node in a UWASN has limited resources, making it necessary to develop a lightweight and accurate method of detection and routing.

This research paper proposed a new system for underwater mine detection based on a cluster-based UWASN. This scheme was designed with low-complexity tasks for the efficient processing of acoustic signals and the accurate detection of mines using a cluster-based Naïve Bayes classifier. It preprocesses the acquired acoustic signals collected from the surrounding environment, using wavelet transform (WT), and then performs the classification based on the extracted features to identify mines. The performance evaluation of each component of the proposed system shows promising results for detection, achieving an accurate mine detection rate of 95.1691% and high energy conservation, attesting to the efficiency of the proposed new detection system. In future work, we believe that this research can be enhanced with the use of the CNN model for classification. We also believe that the use of dense node distribution will help to increase the accuracy; however, the efficiency should be also evaluated with regard to the impact on the activity of ships on the environment. The security of the proposed platform against external attacks also needs to be studied.

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